Optimizing Spectral Power Compression with respect to Inference Performance for Recognition of Tumor Patterns in Ultrasound Images

Sorin Grunwald[1], Victor-Emil Neagoe PhD[2]
[1]Dykonex Corp., Palo Alto, CA
[2] Department of Applied Electronics and Information Engineering, Polytechnic University, Bucharest, Romania

ABSTRACT

Imaging modalities are widely used to explore and diagnose diseases. Feature extraction methods are used to quantitatively describe and identify objects of interest in acquired images, typically involving data compression. The extracted features are subject to clinical inference, whereby the compression ratio used for feature extraction can affect the inference performance. In this paper, a new method is introduced which allows for optimal data compression with respect to performance maximization of uncertain inference. The model introduced herein identifies objects of interest using selective data compression in the frequency domain. It quantifies the amount of information provided by the inference involving these objects, calculates the inference efficiency, and estimates its cost. By analyzing the effect of data compression on inference efficiency and cost, the method allows for the optimal selection of the compression ratio. The method is applied to prostate cancer diagnosis in ultrasound images.

INTRODUCTION

The increased volume and complexity of clinical information and knowledge processing has prompted the development of intelligent agents able to assist the physician in the decision making process. One of the most frequent problems encountered in developing and deploying such assisted diagnostic tools is generated by the need to compromise between their performance and cost. In order to decrease the volume of data and the complexity of data processing compression techniques are frequently used. While potentially reducing cost, such compression techniques may adversely affect the performance of the clinical inference, decision making, and diagnosis because of the simplifications and sometimes increased uncertainty resulting from compression. In this context, a challenge is represented by the relative lack of performance measures, which can be used to consistently guide the design and the deployment of assisted diagnostic tools relative to a required relationship between performance and cost. From a technology development viewpoint, what are needed are quantifiable and reproducible measures for assessing the impact and optimizing the design of data and knowledge compression methods with respect to performance requirements. With respect to the requirements of the healthcare system, what are needed are methods to perform cost-benefit analysis related to the deployment and operation of assisted diagnostic tools.

Imaging modalities are widely used to explore and diagnose diseases. Any imaging modality uses some data compression techniques in order to acquire and represent the images [1]. Different methods are used to quantitatively describe and identify objects of interest in the acquired images. Typically, these methods rely on object feature or signature extraction [2]. Such feature or signature extraction typically involves an implicit data compression, which allows for reducing the large number of dimensions of the initial image representation space to a more manageable number of dimensions in terms of storage and processing. According to [3], in an ultrasound image a prostate tumor is identified by its relatively inhomogeneous structure and hypoechoic character, i.e., its lack of ability to reflect ultrasound. Thus, methods used to represent knowledge related to tumors based on ultrasound images must extract tumor features to reflect this sonographic appearance. Preferably, these methods should also achieve significant data compression. They should allow for information processing in a timely manner with an acceptable level of performance and at an acceptable level of resources and cost. Preferably, performance and cost measures should be available to allow for the optimization of the knowledge representation, i.e., feature extraction with respect to performance and cost. In this paper, a new method is introduced, which correlates performance and cost of clinical inference and analyzes the performance dependency on data compression related to feature extraction.

FEATURE EXTRACTION AND INFERENCE

Figure 1 shows a prostate and a tumor area in an ultrasound image. The objects margins have been identified by an ultrasound specialist. In this paper, a method for tumor representation and detection has been used similar to the method introduced in [4]. The method can extract tumor features during a training stage and can, during a deployment phase, intelligently assist the physician with the clinical inference by identifying prostate tumors areas in the analyzed images.

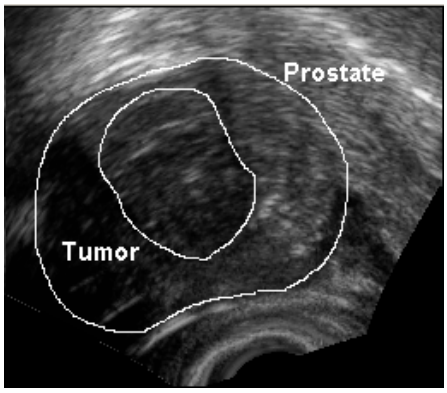

Figure 1: Prostate cancer in an ultrasound image

In the particular test environment used herein the expert user can select an ultrasound image for analysis, which can be, for example, a 2D image chosen from a 3D volume set of images. The user then defines the training region of interest (ROI) to be used for purposes of tumor feature extraction. The tumor features defined herein are the zero frequency (DC) component and the spectral power of the 2D frequency (Fourier) spectrum. The DC component (average intensity) is considered to represent knowledge about the tumor echogenicity. The spectral power is considered to represent knowledge about the tumor structure. The target data compression requirement is specified as a percentage of the 2D spectral power and is called **spectral power compression (SPC**). In the training ROI, the algorithm computes the corresponding 2D Fast Fourier Transform (FFT). Based on the targeted spectral power reduction, the equivalent reduced size of a power compressed ROI is computed such that the equivalent size-reduced ROI contains as much spectral power as targeted by the data compression requirement. The training and the compressed (size-reduced) ROIs are shown in Figure 2. The size-reduced ROI is then automatically moved within the training ROI and the values for the DC component and for the spectral power are collected for each of the reduced ROI positions within the training ROI.

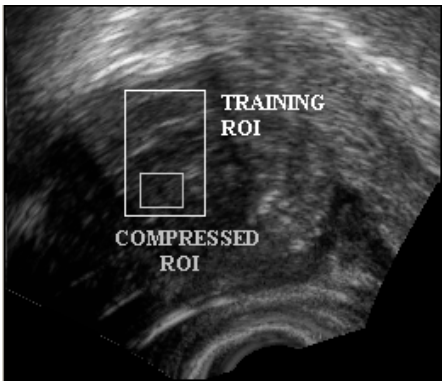

Figure 2: Training and compressed ROIs

The resulting DC component and spectral power average values and ranges are considered to be the tumor's signature. Thus, through the reduced-size ROI, the tumor features have been extracted as a function of the targeted spectral power reduction. The discrimination function applied in this paper is simple: if a ROI has both the DC component and the spectral power falling within the range of the tumor signature detected above then the ROI is classified as a tumor ROI. It is classified as a non-tumor ROI otherwise.

INFERENCE PERFORMANCE

Figure 3 shows the results of applying the tumor classification method for a SPC factor of 0.6 (60%). The area detected by the algorithm as having tumor signs, i.e., tumor signature, is marked *S*s. The original prostate and tumor areas are marked *S*p and *S*t respectively. The overlap area between the tumor area and the area with detected tumor signs is marked *S*ts.

Success Rate

Let *T* denote the event that a tumor is present in the prostate gland and *S* the event that a tumor sign has been detected by the system. The success rate chosen herein is the **positive predictive value (PPV)**, i.e., the probability of inferring that a certain image area belongs to the tumor if the area has been detected as having a tumor sign. The PPV is given by the conditional probability $p(T|S)$.

From geometrical area considerations in Figure 3:

$$PPV = p(T|S) = St s / Ss. \quad (1)$$

Other similar measures of success are described in [5].

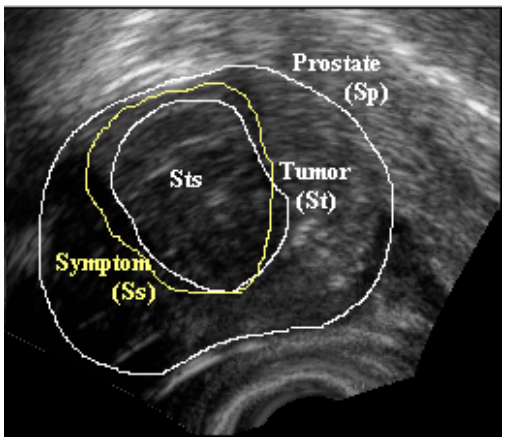

Figure 3: Results of assisted tumor identification

Inference Efficiency

The PPV does not include information about the inference errors nor does it include information about the success relative to the particular image or case under consideration. Borrowing from Information Theory [7] and building on a previously introduced inference performance measures [6], a new performance measure called clinical inference efficiency is introduced herein. The amount of information associated with the presence of tumor in Figure 3 can be calculated as

$$i = - p(T) * \log(p(T)), \quad (2)$$

whereby throughout this paper log means $\log_2$. The probability $p(T)$ can be calculated from Figure 3 from geometrical considerations as

$$p(T) = St / Sp. \quad (3)$$

The information-theoretical concept of mutual information [7] is extrapolated in this paper to describe the amount of information generated by the clinical inference:

$$I = H(\boldsymbol{T}) - H(\boldsymbol{T}|\boldsymbol{S}). \quad (4)$$

whereby extrapolation the information-theoretical equations described in [7], the entropy related to the presence of tumor can be calculated as:

$$H(\boldsymbol{T}) = - p(T)*\log(p(T)) - p(\sim T)*\log(p(\sim T)) \quad (5)$$

and the predictive conditional entropies of tumor and tumor signs as:

$$\begin{aligned} H(\boldsymbol{T}|\boldsymbol{S}) = & - p(S)*p(T|S)*\log (p(T|S)) - \\ & - p(\sim S)*p(T|\sim S)*\log (p(T|\sim S)) - \\ & - p(S)*p(\sim T|S)*\log (p(\sim T|S)) - \\ & - p(\sim S)*p(\sim T|\sim S)*\log (p(\sim T|\sim S)). \end{aligned} \quad (6)$$

The notation $\sim T$ denotes the opposite of T, i.e., the event that a tumor is not present in the prostate gland and $\sim S$ the opposite of S, i.e., the event that no tumor sign has been detected. In geometrical terms, the area described by $\sim T$ is given by $S\sim t = Sp - St$ and the area described by $\sim S$ is given by $S\sim s = Sp - Ss$. The probabilities required by Equations (5) and (6) can be calculated from Equation (1) and from geometrical considerations from Figure 3:

$$p(T) = St/Sp,\ p(\sim T) = (Sp\text{-}St)/Sp = 1\text{-}p(T) \quad (7)$$
$$p(S) = Ss/Sp,\ p(\sim S) = (Sp\text{-}Ss)/Sp = 1\text{-}p(S) \quad (8)$$
$$p(\sim T|S) = 1 - p(T|S) \quad (9)$$
$$NPV = p(\sim T|\sim S) = S\sim t\sim s/S\sim s = \\ = (Sp - St - Ss + Sts) / (Sp - Ss) \quad (10)$$
$$p(T|\sim S) = 1 - p(\sim T|\sim S), \quad (11)$$

whereby NPV stands for the negative predictive value and $S\sim t\sim s$ is the prostate area which is tumor-free and shows not tumor signs. Equation (4) represents an information-theoretical measure for the inference success: the **amount of information generated by the inference**. Compared to the success rate described by Equation (1) the amount of information given by Equation (4) also takes into account the potential errors generated by the inference. The inference information I has a maximum value if the inference is error free. An error free inference is characterized by the following probabilities: $p(T|S) = 1$, $p(\sim T|S) = 0$, $p(\sim T|\sim S) = 1$, and $p(T|\sim S) = 0$. With other words: a tumor sign is observed if and only if a tumor is present. By modifying the SPC value the tumor signature changes. As a result, for each SPC value, the results of the inference may be different and therefore the probabilities described by Equations (1) and (7) to (11) are potentially different. Therefore the inference performance defined by Equations (1) and (4) depends on the SPC value, i.e., on the data compression ratio chosen for the tumor characterization and identification method. The inference capacity C is defined herein as the maximum value of the inference information:

$$C = \max_{SPC}(I), \quad (12)$$

whereby the maximum value of information is considered over all possible SPC values. The **inference efficiency** is defined herein as

$$\eta = I / C. \quad (13)$$

By using Equation (13), a value of the spectral power compression can be chosen, which maximizes the inference efficiency relative to the case under consideration.

Inference Process Cost

Although ignored in many situations, the cost of the inference process is an implicit factor in making design, deployment and utilization decisions. The cost of inference can have many components: the initial investment to purchase the assisted detection algorithm, the cost related to using the algorithms, the cost of algorithm errors, etc. The inference error cost can be minimized by choosing the compression ratio which maximizes the inference efficiency described by Equation (13). For the purposes of this paper, as a measure for the **inference process cost** the computation time required by the inference has been chosen. This cost measure illustrates only one of the aspects of the inference costs mentioned above: the computation time shows how long it takes the system to obtain inference results and is an indication of difficult for the user and therefore how expensive the procedure could be. The computation time for tumor identification is different for each SPC value due to the effect of data compression on the algorithm. The computation time t can be normalized to a value

$$t_n = t / t_{max} \quad (14)$$

with t_{max} representing the maximum computation time considered over the different values of SPC. Equation (14) represents a measure of the inference process cost.

Return-on-Investment

An overall measure called Return-on-Investment (RETI) is introduced in this paper, which can be used to perform cost-benefit analysis related to the inference performance. The Return-on-Investment is defined as the ratio between a measure of success called return over a measure of deployment or operating cost called investment. For the purposes of this paper the inference efficiency given by Equation (13) is used as the measure of success. By using this measure the inference error costs are minimized, i.e., the return is maximized. Equation (14) is used as a measure for the inference cost. It results that the **Return-on-Investment** can be defined as:

$$RETI = \eta / t_n \quad (15)$$

RESULTS AND DISCUSSIONS

Table 1 shows the inference results for different values of SPC for the image in Figure 3. Column CR shows the actual compression ratio in terms of the original vs. the reduced ROI size. The Time column shows the inference time in milliseconds required for tumor detection. Column *S*s in Table 1 shows the area detected by the algorithm as having tumor signs and Column *S*ts shows the size of the overlap area between *S*t and *S*s (Figure 3). According to expert identification, the prostate area *S*p equals 10.28 cm^2 and the tumor area *S*t equals 2.99 cm^2.

Table 1: Inference results

SPC	CR	Time [ms]	*S*s [cm2]	*S*ts [cm2]
0.10	17.02	150	5.69	2.70
0.20	10.88	140	6.39	2.88
0.30	5.76	125	5.33	2.73
0.40	4.14	125	5.68	2.89
0.50	3.03	120	5.68	2.99
0.60	2.37	112	4.18	2.93
0.70	1.85	112	4.67	2.99
0.80	1.50	109	4.62	2.60
0.90	1.16	100	3.27	2.36
0.95	1.03	93	3.77	2.42

Table 2 shows the values for the different inference performance measures defined in this paper as a function of SPC. Figure 4 shows a graphical representation of the different inference performance measures presented in Table 2, whereby "Relative Performance" means any of the defined performance measures and the "Investment Cost" represents the inference process cost. It can be seen that different performance measures are maximized for different SPC values. In the example considered in this paper, the Return-on-Investment is maximized for a SPC value of 0.6. It can also be seen from Table 2 and from Figure 4 that there does not exist a proportional relationship between compression ratio and performance. This happens because the inhomogeneous nature of the tumor structure is selectively reflected in different areas of the spectrum. For example, in Table 2, the success rate is higher for SPC = 0.9 than for SPC = 0.95 because the compression with SPC = 0.9 has eliminated more of the high-frequency components not related to the tumor structure. A decision to choose a certain SPC value should be based on

assessing the relevance of the different performance measures and selecting the appropriate measure given the goals for the study under consideration.

Table 2: Inference performance measures

SPC	Success Rate (PPV)	Inference Efficiency	Inference Process Cost	Return -on- Investment
0.10	0.47	0.36	1.00	0.36
0.20	0.45	0.39	0.86	0.45
0.30	0.51	0.44	0.69	0.64
0.40	0.51	0.54	0.69	0.78
0.50	0.53	0.79	0.64	1.23
0.60	0.70	**1.00**	0.56	**1.79**
0.70	0.64	0.83	0.56	1.48
0.80	0.56	0.49	0.53	0.92
0.90	**0.72**	0.64	0.45	1.42
0.95	0.64	0.54	**0.38**	1.42

In this paper, for illustration purposes the results for only one 2D image have been presented. The method can be applied for multiple 2D images and 3D studies.

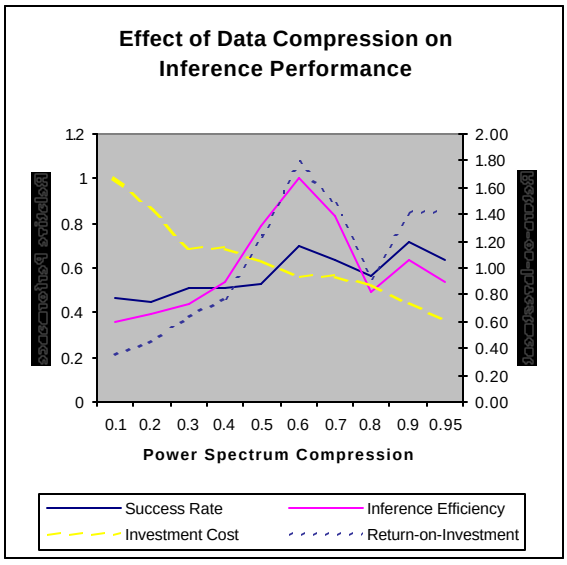

Figure 4: Inference performance chart

In equation (4) only the amount of predictive information has been considered. Rewriting the equation as $I = H(S) - H(S|T)$ in accordance to information theory, the sensitivity $p(S|T)$ and the specificity $p(\sim S|\sim T)$ of the study could be considered. The inference capacity could be defined not over the maximum of inference information for one image but for a whole 3D volume set or for an application type e.g., prostate cancer. The method and the newly introduced performance measures can be applied to any type of objects of interest in any type of images. The cost function could be expanded to include other forms of cost.

CONCLUSIONS

In this paper, a new method has been introduced, which allows for optimized feature extraction and object recognition using selective data compression in the frequency domain. The method quantifies the amount of information provided by the clinical inference using the extracted object features, defines the inference efficiency related to this information, and measures the cost associated with the inference. The Return-on-Investment is introduced as an inference performance measure in order to correlate efficiency and cost. The method further establishes the dependency of inference efficiency, cost, and Return-on-Investment on data compression. The paper shows how data compression ratios can be determined which maximize the Return-on-Investment ratio. The method has been successfully applied to the recognition of prostate tumor patterns in ultrasound images. The herein introduced method is applicable to other types of images and to the recognition of other types of objects used in uncertain inference.

REFERENCES

1. Gonzalez R, Woods R. Digital Image Processing, 2nd ed. Prentice-Hall; 2002.
2. Neagoe V, Stanasila O. Teoria recunoasterii formelor [Pattern Recognition Theory, Ro]. Bucharest: Editura Academiei Romane Publishers; 1992.
3. Rumack CM, Wilson SR, Charboneau JW. Diagnostic Ultrasound, Vol. 1. Mosby; 1998.
4. Grunwald S, inventor; Boston Scientific Corporation, assignee. Method and apparatus for adaptive cross-sectional area computation of IVUS objects using their statistical signatures. US patent 6,120,445. 2000 Sep 19.
5. Russell S, Norvig P. Artificial intelligence: a modern approach. Prentice Hall; 1995.
6. Grunwald S. The efficiency of Bayesian inference. in Diday E, Lechevalier Y, editors. Symbolic-numeric data analysis and learning. New York: Nova Science Publishers; 1991, p. 417-28.
7. Cover T, Joy T. Elements of information theory. John Wiley & Sons; 1991.